Estimating the Exchange Rate Decline via Oil Price Volatility in Azerbaijan

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Azerbaijan is an oil-dependent economy. Although exchange rate is fixed with a non-floating exchange rate, due to the oil price drop in late 2014, the economy faced a severe exchange rate drop in 2015 and 2016. In this paper, we show that the channel which effected this drop is the budget deficit. Firstly, we estimate monthly oil price volatility and then we find a relationship between oil price and the budget deficit. After that, we calculate the relationship between exchange rate and the budget deficit. Finally, we show under what scenarios the exchange rate would drop (and at which rate) due to a potential future oil price shock. The main problem is found in how we calculate exchange rate change once oil prices drop again and how much value the Azerbaijani manat would stand to lose.

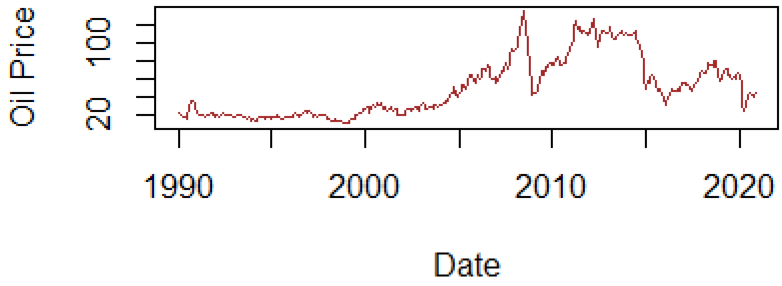
This paper is intended for general audience and policy makers. Moreover, it is good material for students who study economics and econometrics. The topic is interesting because a drop in Azerbaijani manat affects all people residing in Azerbaijan. There are a few articles on this topic like Zulfugarli(2020), but none employ our methodology. We want to estimate exchange rate devaluation due to oil price shock using the budget channel. There is lack of research on this subject. Our methodology will bring a new debate to life. Since there is a lack of research around this topic, we are certain that our paper will ignite new kind of debate in the literature.

Our data consists of a few parts. Firstly, we have monthly oil prices from the 1990s. Those consist of 339 observations. Secondly, we have around 20 macro variables from the 2000s. We need to merge these data in order to create balanced information, which will ensure the consistency and accuracy of our analysis.

We found that oil price shocks (drops in oil prices) will increase the budget deficit. Once we build this relationship, we go into another level of analysis. The next step has two phases: does oil price affect exchange rate directly or through a budget channel? We estimate a meaningful relationship through a budget channel. Our findings show that the budget deficit is negatively correlated with the value of the Azerbaijani manat. As the budget deficit increases, the Azerbaijani manat will lose value.

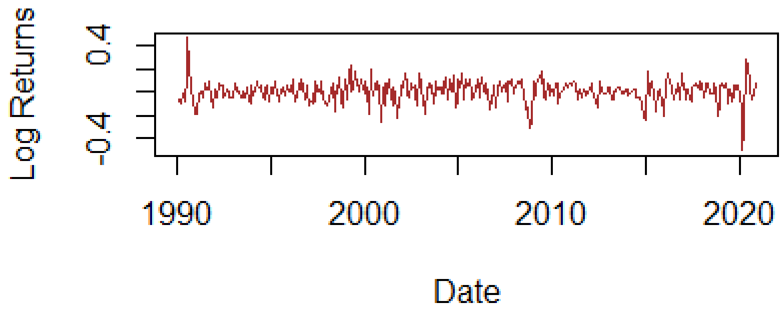
First, we will try to find which volatility model is suitable for our oil price data. We want to explore the threshold value to which oil price would have to drop to create a shock. Once we narrow down a model for this purpose, we will continue to determine relationships between the budget deficit and the exchange rate. Engle (1982) developed the Autoregressive Conditional Heteroskedasticity (ARCH) model, which recognizes the difference between unconditional and conditional variance and lets conditional variance change over time as a function of previous periods' error terms. This technique has the ability to capture the effect of volatility clustering, but it requires a model with a relatively long lag structure, which makes estimation difficult. To make this task easier, Bollerslev (1986) proposed the GARCH model which enables a reduction in the number of parameters by imposing nonlinear restrictions.

Graph 1. Oil Prices



The graph above shows oil price data in levels. The process is automatically chosen as ARIMA(2,1,1). The tests also show that the process is Unit Root. Let us now check log returns of oil prices.

Graph 2. Log Returns of Oil Prices



The graph above shows log returns of oil prices. Looking at the graph we can see that there is some kind of volatility clustering. The process is automatically chosen to be ARIMA(0,0,1), which is MA(1) process. Tests also show that the process is stationary. We will first work on this data to find our best volatility model. We will use rolling window approach to fit our data. It is rather similar to a Value at Risk calculation, and our backtests will rely on this approach. We will calculate errors from each model and compare them to each other. For backtesting, we will use the last 170 observations of our data.

Table 1. Structural GARCH(1,1) results

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VaR Backtest Report
===========================================
Model:                          sGARCH-norm
Backtest Length:         170
Data:


==========================================
alpha:                           1%
Expected Exceed:       1.7
Actual VaR Exceed:     4
Actual %:                      2.40%


Unconditional Coverage (Kupiec)
Null-Hypothesis:         Correct Exceedances
LR.uc Statistic:            2.277
LR.uc Critical:             3.841
LR.uc p-value:             0.131
Reject Null:                  NO


Conditional Coverage (Christoffersen)
Null-Hypothesis:
```

Correct Exceedances and Independence of Failures

LR.cc Statistic: 2.471

LR.cc Critical: 5.991

LR.cc p-value: 0.291

Reject Null: NO

GARCH Roll Mean Forecast Performance Measures

Model: sGARCH

No.Refits: 4

No.Forecasts: 170

Stats

MSE 0.00985

MAE 0.07029

DAC 0.52350

The table above shows the results from a standard GARCH(1,1) model. The tests show that it is suitable for our data. The mean squared error and mean absolute errors have been calculated and reported. We will try other models as well to compare their test results and errors.

Table 2. GJR GARCH Results

VaR Backtest Report

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Model: gjrGARCH-norm

Backtest Length: 170

Data:

==

alpha: 1%

Expected Exceed: 1.7

Actual VaR Exceed: 4

Actual %: 2.40%

Unconditional Coverage (Kupiec)

Null-Hypothesis: Correct Exceedances

LR.uc Statistic: 2.277

LR.uc Critical: 3.841

LR.uc p-value: 0.131

Reject Null: NO

Conditional Coverage (Christoffersen)

Null-Hypothesis: Correct Exceedances and Independence of Failures

LR.cc Statistic: 2.471

LR.cc Critical: 5.991

LR.cc p-value: 0.291

Reject Null: NO

GARCH Roll Mean Forecast Performance Measures

Model: gjrGARCH

No.Refits: 4

No.Forecasts: 170

Stats

MSE 0.009853

MAE 0.070370

DAC 0.511800

The results above are from a GJR GARCH procedure. The tests show that we have a good fit. However, the errors are larger compared to GARCH(1,1).

Table 3. TGARCH (family GARCH) Results

VaR Backtest Report

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Model: fGARCH-norm

Backtest Length: 170

Data:

==

alpha: 1%

Expected Exceed: 1.7

Actual VaR Exceed: 3

Actual %: 1.80%

Unconditional Coverage (Kupiec)

Null-Hypothesis: Correct Exceedances

LR.uc Statistic: 0.818

LR.uc Critical: 3.841

LR.uc p-value: 0.366

Reject Null: NO

Conditional Coverage (Christoffersen)

Null-Hypothesis: Correct Exceedances and Independence of Failures

LR.cc Statistic: 0.926

LR.cc Critical: 5.991

LR.cc p-value: 0.629

Reject Null: NO

GARCH Roll Mean Forecast Performance Measures

Model: fGARCH

SubModel : TGARCH

No.Refits: 4

No.Forecasts: 170

Stats

MSE 0.009725

MAE 0.070120

DAC 0.517600

The table above shows results from the TGARCH procedure from the family GARCH type models. The tests show a good fit for the data. The errors are smaller than GJR GARCH and GARCH(1,1). We therefore choose this threshold GARCH model over others.

VaR Backtest Report

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Model: eGARCH-norm

Backtest Length: 170

Data:

==

alpha: 1%

Expected Exceed: 1.7

Actual VaR Exceed: 3

Actual %: 1.8%

Unconditional Coverage (Kupiec)

Null-Hypothesis: Correct Exceedances

LR.uc Statistic: 0.818

LR.uc Critical: 3.841

LR.uc p-value: 0.366

Reject Null: NO

Conditional Coverage (Christoffersen)

Null-Hypothesis: Correct Exceedances and Independence of Failures

LR.cc Statistic: 0.926

LR.cc Critical: 5.991

LR.cc p-value: 0.629

Reject Null: NO

GARCH Roll Mean Forecast Performance Measures

Model: eGARCH

No.Refits: 4

No.Forecasts: 170

Stats

MSE 0.009822

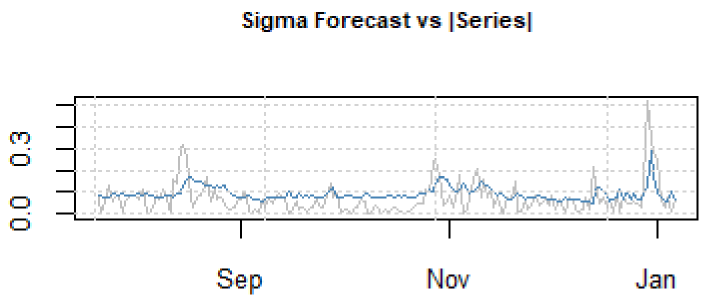
MAE 0.070230

DAC 0.517600

The results above are from an EGARCH(exponential GARCH). The tests show that this model fits the data well. However, the errors are larger than our previous threshold GARCH (TGARCH). There are many more of these type models to estimate, but, in the interest of brevity, we will conclude our modelling of volatility estimates in this phase.

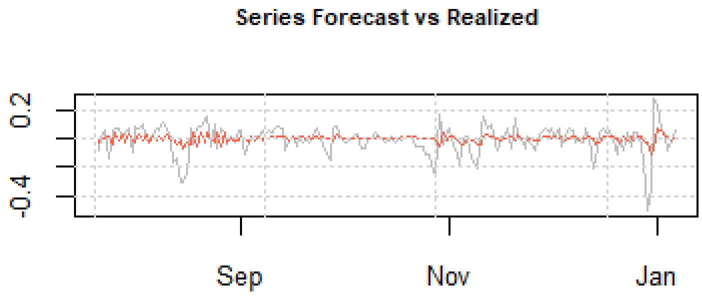
Now we need to calculate the price that would be used as a shock to other variables like the budget deficit and the exchange rate. To remind, we have chosen the threshold GARCH over others as it yields a less erroneous model. Let us look at our chosen TGARCH model more closely.

Graph 3. Volatility Forecast versus Realized Series



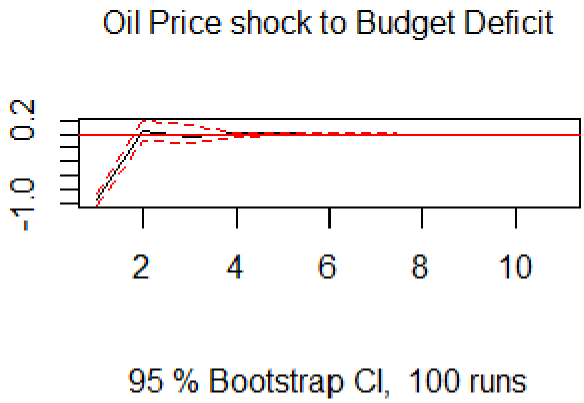
The graph above shows that model is a good fit.

Graph 4. Mean Forecasts versus Realized Means



Mean forecasts also show a good fit for our data. We will use volatility and mean forecasts to determine risky oil prices. That is, we will calculate how much oil price would have to drop to create a shock . Then we will find the relationship between oil prices and the budget deficit (and subsequently with the exchange rate). We will adopt a Vector Auto-Regression (VAR) approach for finding the relationships. The data consists of observations from 2010 to 2018.

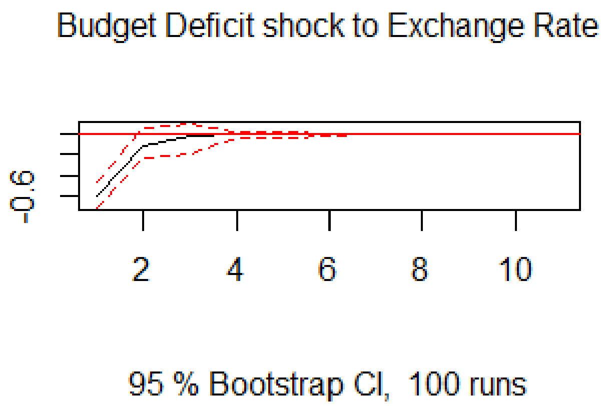
Graph 5. Impulse-Response Function Oil Price-Budget Deficit



The impulse response function above shows the relationship between oil price and budget deficit. The relationship is significant and negative. It means that if oil price drops budget deficit will increase.

Graph 6. Impulse-Response Function Budget Deficit- Exchange

Rate



The impulse-response function above shows a negative relationship between budget deficit and nominal effective exchange rate. It means that if budget deficit increases, nominal exchange rate will drop, and the Azerbaijani manat will lose value.

Lastly, we will combine our previous results and compute exact numbers. We will use volatility and mean forecasts from the previous part and employ VAR equations as relationships.

Volatility estimates show that oil prices would have to drop to 29.4 dollars to create a shock. That is, a 38% drop in oil prices. A 1 per cent drop in oil prices results in a 29.7% increase in the budget deficit. Such an increase in budget deficit would decrease the nominal effective exchange rate by 37.6%. We used the nominal effective exchange rate as a proxy for the usual exchange rate as it is more volatile. As a result, once oil prices drop to approximately 29 dollars, the exchange rate would change to be 2.31 per dollar.

References:

1. Bollerslev, Tim. 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31:

307–27
2. Engle, Robert F. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: Journal of the Econometric Society 50: 987–1007.
3. Zulfugarli, Farid. “The Impact of Oil Price Shocks on The Economy of Azerbaijan: A Vector – Autoregressive Analysis.” Baku Research Institute, March 9, 2020. https://bakuresearchinstitute.org/the-impact-of-oil-priceshocks-on-the-economy-of-azerbaijan/